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Transparency in human-agent teaming and its effect on automation-induced complacency

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Abstract

The battlefield of the future has been envisioned as one soldier operator managing a team of robotic assets to conduct multiple concurrent tasks, and the DoD has been actively investigating the potential of such human-agent teams.Contemporary research shows that one operator managing multiple robotic assets suffers from a variety of performance decrements.Using an intelligent agent as the mediator of the robotic team helps alleviate some problems, while introducing several unique to the supervisory relationship.One such problem is the human-out-of-the-loop condition, which often results in an increase in operator complacent behavior.This proposed study explores how operator knowledge of the work environment and access to the agent's reasoning affects complacent behavior.Additionally, the interaction of operator knowledge and agent reasoning will be explored to see how the presence (or lack thereof) of each affects operator performance, workload, and situation awareness.

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*Keywords:*Human-agent teaming; Supervisory control; Agent transparency; Individual differences

1. Introduction

In many dynamic environments, multiple human operators oversee single robots conducting complex tasks.Teams of operators oversee and control a single military drone.Emergency responder teams operate a single robot to search disaster areas for potential survivors or to identify potential hidden dangers.It is currently common

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practice for aerial systems to have a many operators to one system ratio, and for ground systems a two-to-one ratio is preferred [1].However, this many-to-one model is burdensome and unwieldy, requiring multiple human operators to oversee and manage a single robotic entity.A preferable arrangement would be a single human operator overseeing multiple robotic entities (one-to-many), in this manner productivity for the human would be enhanced, rather than reduced/distributed, as in the many-to-one model.

The battlefield of the future has been envisioned as one soldier operator managing a team of robotic assets to conduct multiple concurrent tasks, and the Department of Defence (DoD) has been actively investigating the potential of such human-agent teams [2].Research has shown that a single operator managing multiple robotic assets suffered performance decrements, reduced situation awareness (SA) and increased workload [3].The more robots the operator must interact with individually, the greater the performance decrement.Incorporating an intelligent agent to mediate between the human operator and the robotic assets allows the operator to manage the robotic team better while performing other duties [4].One such intelligent agent, RoboLeader, was developed to assist a human operator manage a team of robots, and several subsequent studies have shown that utilizing such an agent improved operator's SA and task performance while decreasing their perceived workload [5, 6].

The addition of an intelligent agent to manage the robotic team brings its own unique problems.While the operator benefits from reduced workload, findings indicate they do not always improve on task performance and SA.One study found no difference in target detection performance between the Baseline and RoboLeader conditions, although there was an improvement in mission completion times [7].Similar findings were reported in a more recent study, in that increasing RoboLeader's level of autonomy (LOA) did not always improve SA or task performance, and in some cases, performance in the highest LOA decreased [8].Whether this was due to automation-induced complacency [9] or the operator recognizing they lacked enough information to override knowledgeably the agent suggestion was not clear.When the intelligent agent is managing vehicle tasking, route planning, or managing vehicles of differing constraints and capabilities, it becomes even more challenging to effectively convey information to the supervising operator in a manner that allows them to assimilate the information and stay engaged in their supervisory task [10].Transparency of the agent's intent and reasoning may encourage the operator to stay engaged and in-the-loop, improving performance and reducing complacency.

However, agent transparency does not exist in a vacuum.A supervisor requires understanding of the task objectives and the task environment in addition to insight into the agent's behaviour and intents.This is particularly important in an evolving environment, where the operator's goals may not always be in agreement with the agents' goals [11].When specific environmental information or the agent's reasoning is not available to the operator, the operator has no reason to participate in the decision-making process, thus encouraging a human-out-of-the-loop situation [12, 13], which could be mistaken for automation-induced complacency [14].Complacent behaviour occurs when factors create conditions that favour inaction or continued repetitive action on the part of the operator.

Access to environmental information alone may not be enough to keep the operator engaged.To effectively supervise an agent's action, the human operator requires not only knowledge of the task environment, but insight into the agent's reasoning process as well.A recently published model of Situation awareness-based Agent Transparency (SAT) [15] has levels that correspond to Endsley's [16] environmental SA model, but also incorporates Lee and See's [17] "three P's" (i.e., purpose, process, and performance) framework for human-agent trust development.The SAT model describes knowledge of what is happening in the environment and the agent's goals as supporting the operators' Level 1 SA (i.e., what is the agent trying to do), understanding the agent's reasoning process as supporting the operators' Level 2 SA (i.e., why does the agent do it), and providing future projections, likelihood of success, and uncertainty information as supporting the operators' Level 3 SA (i.e., what should happen) [18].When the operator has knowledge of the agents' intent, understands the agents' reasoning, and can anticipate likely outcomes based on the information and reasoning, the operator can properly calibrate their trust in the agent [19].

2. Study objective

Current DoD research [20, 21] explores the relationship between access to information and decision-making, within the framework of the SAT model, in static single-task environments.This research proposes to investigate these factors using a dynamic, multi-tasking simulation that emulates a Soldier's real-world task environment.A key finding of an earlier study [22] was that adding uncertainty information increased operator trust in the system.However, due to the dynamic nature of this study environment, adding uncertainty information is expected to reduce operator trust in the system in the current study.Specifically, this proposed study will investigate how knowledge of the current state of the environment, access to agent reasoning, and uncertainty information interact to affect the human operators' performance on a route planning task, operator workload, and SA.

3. Studyoverview

This experiment simulates a multitasking environment where the operator has to supervise an autonomous agent's route revision recommendations for a convoy of three vehicles (his/her own manned ground vehicle [MGV], an unmanned aerial system [UAS], and an unmanned ground vehicle [UGV]) as it proceeds along a predetermined route through an urban environment.As the convoy progresses, events (e.g., threats present, environmental hazards/obstacles) will occur that may necessitate altering the convoy's route (either to go investigate a point of interest or to avoid a potentially hazardous situation).RoboLeader will automatically suggest a potential route revision, and the operator will either have to accept the suggestion, or reject it and keep the convoy on its original path.Markers will appear on the map, indicating such events as enemy movement, enemy numbers, environmental factors (such as unpaved roads or potential IEDs), etc.Operators will also have access to Intel messages from command, which call attention or further explain specific events already indicated by the map markers.When the information indicates that the route suggestion from RL is inappropriate, the operator will need to reject RL's suggestion.In addition to the supervisory duties, participants must maintain local security around the convoy via the vehicles' indirect-vision camera feeds by reporting any threats present in the immediate vicinity of the convoy (target detection task).Participants will also be required to maintain situational awareness, and will receive SA queries throughout each trial.

3.1. Experimental design and independent variables

The proposed study is a 2 x 3 mixed between-within subjects experiment.The between-subjects factor is Level of Environmental Information (LEI).In the Low LEI condition, minimal information regarding the convoy's environment is available to the participant.In the High LEI condition, additional, sometimes competing, information about the convoy environment is available.Participants will be randomly assigned to one of the two LEI conditions.LEI is manipulated via markers on the map, identifying potential hazards and their area of influence.

The within-subjects factor is Level of agent Reasoning (LOR).In the Low LOR condition, the agent will recommend a course of action but will otherwise offer no insight as to the reasoning behind the recommendation.In the Med LOR condition, the agent will recommend a course of action and will give the reason behind this recommendation.In the High LOR condition, the agent recommendation will include the rationale behind the decision, as well as the recency of the information supporting the recommendation.Participants will complete three missions, one in each LOR.LOR will be randomized across conditions and counterbalanced across participants using a modified Latin Squares design.LOR is manipulated via agent messages.

Several individual difference factors and their effect on operator performance will also be evaluated in the current study.Persons with higher perceived attentional control (PAC) have been found to be more effective in allocating attention, and less susceptible to performance degradation in a multitasking environment than those with low PAC [23, 24, 25].Spatial ability (SpA) has been found to have differential effects on teleoperation tasks, robotic operation, and target detection tasks [26, 27, 28].Differences in working memory capacity (WMC) have been shown to affect performance in multi-robot supervisory tasks [29].In the current experiment, we will examine the differential effects of PAC, SpA, and WMC on multitasking performance, operator SA, and perceived workload.Potential for complacency (CP) [30] has been found to affect an individual's ability to adequately monitor automation and to detect automation failures, so CP will be examined as a mediating factor in the route selection task.

3.2. Dependent measures

The following dependent measures will be collected for analysis:

- Route Selection Task Measures:
  - Score: Participants will be scored on whether they correctly accepted or rejected RoboLeader's route selection.Incorrect accepts are indicative of complacent behavior, while incorrect rejects are indicative of low trust and/or poor SA.
  - Decision Time: Decision time is expected to increase as LEI and LOR increase.Reduced decision time while LEI and LOR are increasing could indicate overwork, resulting in complacent behavior.
- Target Detection Task Measures:
  - Targets correctly detected (percentage): Number of targets correctly identified is expected to decrease in overwork conditions.
  - Number of False Alarms: Number of false alarms is expected to increase as workload increases.
  - A' – A measure of sensitivity to target. A' values near .5 indicate correct detection probability near chance, while higher values of A' indicate increased discernibility of targets and participant sensitivity to targets.
  - Beta – The likelihood ratio, a measure of response bias. Higher values of Beta indicate a more conservative response bias.

Situation Awareness Scores: Each mission contains 18 SA queries, 6 for each of the three SA levels. SA queries are designed to assess the participants' SA at a specific SA level (i.e. SA1 – level 1 SA, perception; SA2 – level 2 SA, reasoning, comprehension; SA3 - level 3 SA, projection of future state).

Perceived workload – The NASA-TLX [31] will be administered after each mission.

Trust – The Usability and Trust Survey [32] will be administered after each mission to assess the participants' trust in the agent.

3.3. Hypotheses

The following hypotheses are posited:

H1: Increasing the operator's knowledge of their surroundings will decrease complacent behaviour

H2: Increasing access to agent reasoning will also result in reduced complacent behaviour,

H3: When environmental information is limited, increased access to agent reasoning will improve performance, improve SA scores, increase workload, and increase trust in the agent, however will negatively impact performance on the target detection task.

H4: When environmental information is high, increased access to agent reasoning will improve performance on the route selection task, improve level 2 & 3 SA scores, increase workload, and increase trust in the agent, however will negatively impact performance on the target detection task and reduce level 1 SA scores.

H5: Adding uncertainty information to agent reasoning will negatively impact performance in the route selection and target detection tasks, reduce SA scores, decrease trust in the agent, and increase workload.

4. Conclusion

Results of this study are expected to elucidate the relationship between an operators' knowledge of their environment and the agents' level of reasoning, and how these interact to affect operator performance, workload, and complacency.In addition, these findings will enhance our understanding of how operator knowledge and agent reasoning work together to influence operator SA.

Operator performance can be enhanced with proper training, and intelligent agents can be designed to be more transparent.However, there is a limit to how much training an operator can have, and what the expected increase in performance will be as a result of continued training.Conversely, while designing an agent to be more transparent is often a goal of the designer, identifying how much 'transparency' is required to enhance operator performance while reducing workload and complacent behaviour is often a nebulous target.Understanding the relationship between operator knowledge and agent transparency will help future designers identify how much of each is necessary for the most favourable outcome.

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